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MODELING AND FORECASTING OF GROSS MILK YIELD USING MODERN METHODS OF TIME SERIES ANALYSIS

МОДЕЛЮВАННЯ ТА ПРОГНОЗУВАННЯ ВАЛОВОГО НАДОЮ МОЛОКА З ВИКОРИСТАННЯМ СУЧАСНИХ МЕТОДІВ АНАЛІЗУ ЧАСОВИХ РЯДІВ

The article considers approaches to modeling and forecasting gross milk yield based on modern methods of time series analysis. The development of forecasting methods in the agro-industrial sector is an important task, since effective management of milk production allows optimizing resources, reducing losses and increasing the profitability of enterprises. Two approaches were used to implement the forecasting models: SARIMAX and Prophet – time series models. A comparative analysis of the accuracy of these models was conducted using evaluation metrics such as RMSE, MAE, MAPE and MASE. The results of the study showed that the Prophet model demonstrated higher forecasting accuracy, especially for long-term trends and seasonal changes. The results obtained can be used to plan production processes in the dairy sector, manage feed stocks, and determine optimal enterprise development strategies.

Keywords: *milk production, time series, forecasting, data analysis, predictive analytics.*

У статті розглянуто підходи до моделювання та прогнозування валового надою молока на основі сучасних методів аналізу часових рядів. Розвиток методів прогнозування в агропромисловому секторі є важливим завданням, оскільки ефективне управління виробництвом молока дозволяє оптимізувати ресурси, зменшити втрати та підвищити рентабельність підприємств. У дослідженні проведено аналіз даних про надої молока за попередні роки, виявлено основні тенденції та сезонні закономірності. Для реалізації прогнозних моделей використано два підходи: SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors) та Prophet – інструмент для роботи з часовими рядами, що дозволяє враховувати сезонність, свята та довгострокові тренди. Проведено порівняльний аналіз точності цих моделей, використовуючи такі метрики оцінювання, як RMSE (середньоквадратична похибка), MAE (середня абсолютна похибка), MAPE (середня абсолютна похибка) та MASE (масштабована абсолютна відносна похибка). Результати дослідження показали, що модель Prophet продемонструвала вищу точність прогнозування, особливо щодо довгострокового тренду та сезонних змін. Це підтверджується нижчими значеннями метрик похибки у порівнянні з SARIMAX. Аналіз компонент моделі виявив чітку сезонність у зміні надою молока: максимальні обсяги спостерігаються у літньо-осінній період, тоді як зимові місяці характеризуються спадом виробництва. Прогнозування на два роки вперед вказує на позитивний тренд зростання валового надою молока, що може бути результатом покращення технологій утримання худоби, ефективнішого використання кормової бази та інших факторів. Водночас, аналіз довірчих інтервалів показує, що з розширенням горизонту прогнозування невизначеність зростає, що необхідно враховувати при ухваленні управлінських рішень. Отримані результати можуть бути використані для планування виробничих процесів у молочному секторі, управління запасами кормів та визначення оптимальних стратегій розвитку підприємств.

Ключові слова: *виробництво молока, часові ряди, прогнозування, аналіз даних, прогнозна аналітика.*

Formulation of the problem. The dairy industry is one of the key components of the agro-industrial complex, providing the population with valuable food products, creating jobs and contributing to economic development. Research in this area is of particular relevance due to a number of economic, technological, environmental and social factors.

Effective planning and management of the dairy industry requires accurate forecasts of milk production, as its production volume (gross yield) depends on numerous factors: seasonality, climate change, feed base, livestock productivity and economic conditions. The lack of accurate forecasting models can lead to an imbalance between demand and supply, which negatively affects pricing, producer profitability and the stability of the dairy market.

Traditional forecasting methods often fail to account for complex data structures, including nonlinear relationships, long-term trends, and seasonal variations. Using modern time series analysis approaches based on Prophet and SARIMAX libraries allows for more accurate forecasts through Bayesian modeling and autoregressive methods.

The main challenge is the need to develop and evaluate models that can effectively predict gross milk yield, taking into account seasonality, economic fluctuations, and other influencing factors. This will contribute to improved production planning, resource optimization, and increased economic sustainability of the dairy industry [1, 3].

The research conducted in this paper is aimed at developing a predictive model based on modern methods of time series analysis, which will provide more accurate estimates of future milk production and allow agricultural enterprises and politicians to make more informed decisions.

Analysis of recent research and publications. The work [11] Hladiy M. and Prosovych O. examined the current state and development trends of the dairy industry in Ukraine. The main production indicators of dairy cattle breeding over the past thirty years were analyzed. It was concluded that the introduction of an effective mechanism for implementing the proposed strategic measures, subject to state support and increased funding, will become the driving force for the accelerated development of the dairy industry. Uzhva A. in [19] analyzed the indicators of the state of milk production in Ukraine in modern conditions and developed practical recommendations for supporting the functioning of agricultural enterprises engaged in livestock breeding. Donets L. et al in [7], Svynous I. et al in [18] considered the trends in the development of the milk market in Ukraine. Hansen B. [9], O'Leary C., Lynch C [15], Salamone M. in [16] considered various machine learning approaches for predicting milk production volumes.

Atalan A. in [2] performed drinking milk price forecasting using machine learning algorithms, taking into account economic, social, and environmental factors. Five ML algorithms, including random forest, gradient boosting, support vector machine (SVM), neural network, and AdaBoost algorithms, were utilized to predict the drinking milk unit price. ML also applied hyperparameter tuning with nested cross-validation to calculate the prediction accuracy for each algorithm. The results show that the random forest algorithm based on the features of the ML algorithms has the best performance. Hayes E in [10] investigated trends and forecasting of seasonal changes in milk composition in pasture systems. The study emphasizes the influence of factors such as weather conditions and grass growth on the milk composition of a herd. The ability to predict changes in milk composition at different stages of lactation provides advantages to processors, helping to optimize the logistics of internal production and supply of dairy products.

Bovo M., Giannone C., Moore S in the works [6, 8, 13] machine learning models are proposed to increase the stability of the dairy sector of the economy. Li M. in [12] forecasted the volume of milk and milk components in the US states. Time series decomposition was used to obtain the annual trend of each state and the seasonal structure of milk productivity for each parity. The works Baswaraju S., Bazrafshan O. and Nosratabadi S. [4–5, 14], are devoted to forecasting food production using machine learning algorithms.

Despite the large number of works devoted to the study of the dairy market, the problems of medium-term forecasting using modern methods of time series analysis remain relevant and require further research.

Formulation of the article's objectives. The purpose of this work is to compare the effectiveness of different methods of time series analysis for forecasting milk production for a period of two years, as well as to provide recommendations on the application of the most effective method for practical needs in agriculture.

Presentation of the main material. *Data Overview.* The research data on the volume of milk production (gross milk yield) for the period from January 1, 2008 to December 1, 2024 were obtained from the website of the Main Department of Statistics in the Khmelnytskyi region of Ukraine [17].

Prophet. This is an additive time series forecasting model that focuses on ease of use, high accuracy, and adaptability to seasonality and changes in the data. This model is widely used to analyze data with a pronounced seasonal component, trends, and events that can affect the dynamics of the series. It consists of the following components:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t. \tag{1}$$

Here *g(t)* is the linear trend of the:

$$g(t) = (k + a(t)\delta)t + b, \tag{2}$$

where *k* is the base growth rate, *a(t)* is the trend change indicator, δ is the trend speed change, *s(t)* is a seasonal component.

Fourier series are used to describe seasonality:

$$s(t) = \sum_{n=1}^{N}\left[a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right] \tag{3}$$

where *P* is the seasonality period, *h(t)* is responsible for the given anomalous days (external events or holidays) that have a significant impact on the time series, ϵ_t is the error that contains information not taken into account by the model.

Stochastic gradient descent was used to estimate the parameters.

Prophet is implemented using the prophet library *(Python)*. The input data for the model is a time series in DataFrame format with columns *ds* (date) and *y* (value). The result is a forecast with the ability to visualize components (trend, seasonality, events).

SARIMAX. The *SARIMAX* model (Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors) is an extended version of *SARIMA*, which is used to model time series with seasonality, trends and the influence of external factors. It is one of the most popular models, combining the advantages of statistical analysis and the ability to take into account external regressors. *SARIMAX* combines several key components: autoregression, integration, moving average, seasonality, exogenous variables.

SARIMAX can be written as follows:

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D y_t = \\ = \Theta_q(B^s)\theta_p(B)\varepsilon_t + X_t\beta \tag{4}$$

where B is the shift operator; y_t – is the value of the time series at time t; ε_t is the residuals (noise); X_t, β is the contribution of exogenous variables.

To build a model, the series must be tested for stationarity using the Dickey-Fuller (ADF) test. The model parameters are selected using an automatic selection algorithm (AIC/BIC). The maximum likelihood method is used to estimate the parameters.

To assess the quality of time series forecasting, the following metrics are used in this study:

root mean square error (*RMSE*)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - F_i)^2}, \tag{5}$$

mean absolute error (*MAE*)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|E_i - F_i|, \tag{6}$$

mean absolute percentage error (*MAPE*)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|E_t - F_t|}{E_t}\cdot 100\%, \tag{7}$$

and mean absolute scaler error (*MASE*)

$$MASE = \frac{MAE}{\frac{1}{n-1}\sum_{i=2}^{n}|E_i - E_{i-1}|} \tag{8}$$

where E_i and F_i are the actual and predicted values, n is the number of values.

Let us consider the dynamics of changes in milk production volumes (gross milk yield) from January 2008 to December 2024 in the Khmelnytskyi region (Figure 1).

Figure 1 shows regular fluctuations in milk production, which indicates the influence of seasonal factors, in particular weather conditions and lactation cycles of cows. The general trend shows that the average level of production remained approximately stable with possible minor changes. In the periods 2015–2016 and 2022–2023, significant fluctuations can be observed, which may be caused by changes in production technologies, economic factors or crisis situations in agriculture.

Table 1 contains statistical characteristics of milk production volumes (thousand tons), corresponding to the period from January 2008 to December 2024. A relatively large standard deviation indicates significant fluctuations in production, which is explained by seasonality.

A skewness value close to zero indicates an almost symmetric distribution of the data relative to the mean, which means a balanced influence of extreme values without a significant shift in the distribution. A negative value of kurtosis indicates that the distribution is characterized by less pronounced peaks and a smoother distribution of values compared to a normal distribution.

To assess the forecasting quality of each model, the original data (204 months) was divided into a training (180 months) and a test set (24 months). The test set data was compared with the obtained forecasts of the *Prophet* and *SARIMAX* models using the *RMSE*, *MAE*, *MAPE*, *MASE* metrics (Table 2).

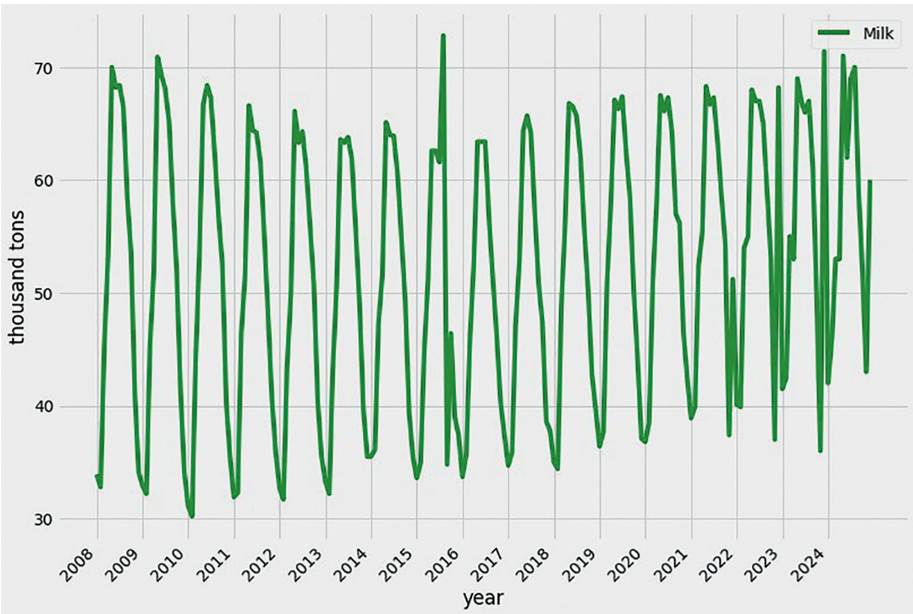

Figure 1. Dynamics of changes in milk production volumes (gross milk yield) from January 2008 to December 2024 in Khmelnytskyi region

Source: authors' elaboration from [17]

Table 1

Statistical characteristics of milk production volumes, thousand tons

Metrics	N	Mean	Std.	Min.	Max.	Skew.	Kurt.
Milk	204	52	12.16	30.20	72.8	-0.14	-1.32

Source: authors' elaboration

Table 2

Evaluating the quality of forecasting models for 2 years

	rmse	mae	mape	mase
sarimax	3.663	2.978	5.563	0.309
prophet	3.005	2.247	4.421	0.377

Source: authors' elaboration

Analyzing the metrics in the table, we can draw the following conclusions: the *Prophet* model has lower *RMSE* and *MAE* values compared to *SARIMAX*, which indicates a smaller average error and better overall forecast accuracy. The *MAPE* value is also lower for *Prophet,* which means more accurate forecasting in relative terms. However, the *MASE* score is lower for *SARIMAX*, which indicates a more stable behavior of this method relative to the baseline model.

Overall, the Prophet model shows higher prediction accuracy in the main metrics *RMSE*, *MAE* and *MAPE*, making it more suitable for predicting gross milk yield. However, the lower *MASE* value in *SARIMAX* may indicate its stability in long-term predictions.

Figure 2 shows the predicted and actual values of gross milk yield. The black dots are the actual values of milk yield, the blue line is the forecast obtained by the Prophet model, and the light blue area is the confidence interval (probable range of the forecast).

The forecast reflects the general trend well – the model captures both long-term growth and annual seasonal fluctuations. The data has high variability – at some points the model may underestimate or overestimate the actual values, which may be due to the influence of unpredictable factors (weather conditions, changes in production, etc.). The confidence interval increases in the future, which is natural for forecasting models – the further into the future, the higher the uncertainty.

In general, both models model the trend and seasonality well, which allows for high-quality forecasts. Seasonal fluctuations are significant, and this should be taken into account when planning production. The forecast shows a stable increase in milk yield, which is a positive signal for the industry. The models can be improved by taking into account additional factors (temperature, feed, technological changes) to reduce discrepancies between actual and forecast values.

Conclusions. In this work, modeling and forecasting of gross milk yield using the *SARIMAX* and *Prophet* models was carried out. The use of modern methods of time series analysis allows achieving high forecasting accuracy.

Comparative analysis of the models showed that *Prophet* has lower *RMSE*, *MAE* and *MAPE* values, indicating a higher average forecast accuracy compared to *SARIMAX*. Gross milk yield shows pronounced seasonality and a long-term growth trend. Analysis of the components of the time series confirmed that the largest volumes of milk yield fall on the summer-autumn period, while a decline is observed in the winter months. The overall trend indicates a gradual increase in production.

The *Prophet* model demonstrated higher accuracy in forecasting the general trend and seasonal variations, while *SARIMAX* was more stable relative to the baseline model, as evidenced by the lower *MASE* value. This indicates its potential advantages for long-term forecasting. Forecasting for two years ahead showed a stable increase in yield, however, increasing the forecast horizon increases the level of uncertainty, as evidenced by the widening of the forecast confidence interval.

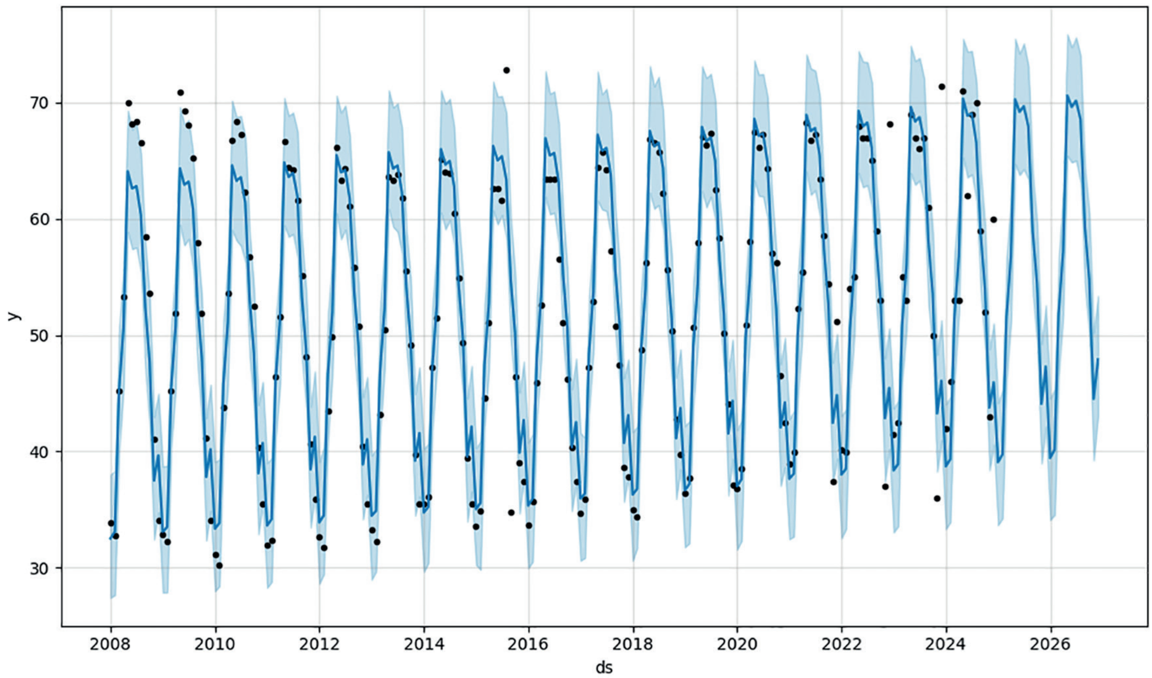

Figure 2. Forecast and actual values of milk production (gross milk yield)

The choice of *SARIMAX* and *Prophet* models in this work is due to their ability to effectively model seasonal fluctuations and long-term trends. Further research can focus on improving the forecasting models by taking into account additional factors, including weather conditions, changes in the structure of feeds, genetic characteristics of animals and technological innovations in milk production. A promising direction for further research is also the use of more complex methods, in particular neural networks (*LSTM*, *GRU*), to increase the accuracy of forecasting.

The results obtained can be used to optimize milk production management, resource planning, and improve the efficiency of the dairy industry.

References:

1. Abuselidze G., Talavyria M., Vyshnivska B., Bondarenko L., Makedon H., Kniazieva T., Salkova I. (2023) The economic mechanism of marketing activity management of food enterprises. In *E3S Web of Conferences*, vol. 371. DOI: https://doi.org/10.1051/e3sconf/202337105002

2. Atalan A. (2023) Forecasting drinking milk price based on economic, social, and environmental factors using machine learning algorithms. *Agribusiness*, vol. 39(1), pp. 214–241. DOI: https://doi.org/10.1002/agr.21773

3. Babyna O., Babyn, I. (2022) Organization of marketing activities at milk-processing enterprises of Ukraine. *Monograph. Primedia eLaunch, Boston*, USA, pp. 72–107. DOI: https://doi.org/10.46299/979-8-88680-819-3

4. Baswaraju S., Maheswari V., Chennam K., Thirumalraj A., Kantipudi M., Aluvalu R. (2023) Future food production prediction using AROA based hybrid deep learning model in agri-sector. *Human-Centric Intelligent System*s, vol. 3(4), pp. 521–536. DOI: https://doi.org/10.1007/s44230-023-00046-y

5. Bazrafshan O., Ehteram M., Latif S., Huang Y., Teo F., Ahmed A., El - Shafie A. (2022) Predicting crop yields using a new robust Bayesian averaging model based on multiple hybrid ANFIS and MLP models. *Ain Shams Engineering Journal,* vol. 13(5). DOI: https://doi.org/10.1016/j.asej.2022.101724

6. Bovo M., Agrusti M., Benni S., Torreggiani D., Tassinari P. (2021) Random Forest Modelling of Milk Yield of Dairy Cows under Heat Stress Conditions. *Animals*, vol. 11(5). DOI: https://doi.org/10.3390/ani11051305

7. Donets L. Ya., Rodina O. B., Kurbatska L. M. (2024) Tendentsii rozvytku rynku moloka v Ukraini [Trends of Development of Milk Market in Ukraine]. *Problems of Modern Transformations. Series: Economics and Management*, no. (11). DOI: https://doi.org/10.54929/2786-5738-2024-11-03-04

8. Giannone C., Bovo M., Ceccarelli M., Torreggiani D., Tassinari P. (2023) Review of the Heat Stress-Induced Responses in Dairy Cattle. *Animals*, vol. 13(22). DOI: https://doi.org/10.3390/ani13223451

9. Hansen B., Li Y., Sun R., Schei I. (2024) Forecasting milk delivery to dairy–How modern statistical and machine learning methods can contribute. *Expert Systems with Applications*, vol. 248. DOI: https://doi.org/10.1016/j.eswa.2024.123475

10. Hayes E., Wallace D., O'Donnell C., Greene D., Hennessy D., O'Shea N., Fenelon M. (2023) Trend analysis and prediction of seasonal changes in milk composition from a pasture-based dairy research herd. *Journal of Dairy Science*, vol. 106(4), pp. 2326–2337. DOI: https://doi.org/10.3168/jds.2021-21483

11. Hladiy M., Prosovych O. (2022) Suchasnyi stan ta perspektyvy rozvytku molochnoi haluzi Ukrainy [Current state and prospect development of the dairy industry in Ukraine]. *Bulletin of Lviv Polytechnic National University series: "Economics and Management Issues"*, vol. 6(2), pp. 20–31. DOI: http://doi.org/10.23939/semi2022.02.020

12. Li M., Reed K., Cabrera V. (2023) A time series analysis of milk productivity in US dairy states. *Journal of Dairy Science*, vol. 106(9), pp. 6232–6248. DOI: https://doi.org/10.3168/jds.2022-22751

13. Moore S., Costa A., Penasa M., Callegaro S., De Marchi M. (2023) How heat stress conditions affect milk yield, composition, and price in Italian Holstein herds. *Journal of Dairy Science*, vol. 106(6), pp. 4042–4058. DOI: https://doi.org/10.3168/jds.2022-22640

14. Nosratabadi S., Ardabili S., Lakner Z., Mako C., Mosavi A. (2021) Prediction of food production using machine learning algorithms of multilayer perceptron and ANFIS. *Agriculture*, vol. 11(5). DOI: https://doi.org/10.3390/agriculture11050408

15. O'Leary C., Lynch C. (2022) An evaluation of machine learning approaches for milk volume prediction in Ireland. In *2022 33rd Irish Signals and Systems Conference*, pp. 1–8. DOI: https://doi.org/10.1109/ISSC55427.2022.9826160

16. Salamone M., Adriaens I., Vervaet A., Opsomer G., Atashi H., Fievez V., Hostens M. (2022) Prediction of first test day milk yield using historical records in dairy cows. *Animal*, vol. 16(11). DOI: https://doi.org/10.1016/j.animal.2022.100658

17. Holovne upravlinnia statystyky v Khmelnytskii oblasti [State Statistics Service of Ukraine. Main Department of Statistics in Khmelnytskyi Region]. Available at: https://www.km.ukrstat.gov.ua/ukr/index.htm

18. Svynous I., Ibatullin M., Salo I., Radko V., Semysal A. (2022) Orhanizatsiino-ekonomichni zasady funktsionuvannia rynku moloka [Organizational and economic bases of milk market functioning]. *Food resources*, vol. 10(18), pp. 276–286. DOI: https://doi.org/10.31073/foodresources2022-18-27

19. Uzhva A. (2024) Analitychnyi monitorynh stanu vyrobnytstva moloka v Ukraini [Analytical monitoring of milk production in Ukraine]. *Ukrainian Journal of Applied Economics and Technology*, vol. 9(2), pp. 236–239. DOI: https://doi.org/10.36887/2415-8453-2024-2-40

Література:

1. Abuselidze G., Talavyria M., Vyshnivska B., Bondarenko L., Makedon H., Kniazieva T., Salkova I. The economic mechanism of marketing activity management of food enterprises. In *E3S Web of Conferences*, 2023. V. 371. DOI: https://doi.org/10.1051/e3sconf/202337105002

2. Atalan A. Forecasting drinking milk price based on economic, social, and environmental factors using machine learning algorithms. *Agribusiness*, 2023. Vol. 39(1). PP. 214–241. DOI: https://doi.org/10.1002/agr.21773

3. Babyna O., Babyn, I. Organization of marketing activities at milk-processing enterprises of Ukraine. *Monograph. Primedia eLaunch, Boston*, USA, 2022. PP. 72–107. DOI: https://doi.org/10.46299/979-8-88680-819-3

4. Baswaraju S., Maheswari V., Chennam K., Thirumalraj A., Kantipudi M., Aluvalu R. Future food production prediction using AROA based hybrid deep learning model in agri-sector. *Human-Centric Intelligent Systems*. 2023. Vol. 3(4). PP. 521–536. DOI: https://doi.org/10.1007/s44230-023-00046-y

5. Bazrafshan O., Ehteram M., Latif S., Huang Y., Teo F., Ahmed A., El - Shafie A. Predicting crop yields using a new robust Bayesian averaging model based on multiple hybrid ANFIS and MLP models. *Ain Shams Engineering Journal*. 2022. Vol. 13(5). DOI: https://doi.org/10.1016/j.asej.2022.101724

6. Bovo M., Agrusti M., Benni S., Torreggiani D., Tassinari P. Random Forest Modelling of Milk Yield of Dairy Cows under Heat Stress Conditions. *Animals*. 2021. Vol. 11(5). DOI: https://doi.org/10.3390/ani11051305

7. Донець Л. Я., Родіна О. В., Курбацька Л. М. Тенденції розвитку ринку молока в Україні. *Проблеми сучасних трансформацій. Серія: економіка та управління.* 2024. № 11. DOI: https://doi.org/10.54929/2786-5738-2024-11-03-04

8. Giannone C., Bovo M., Ceccarelli M., Torreggiani D., Tassinari P. Review of the Heat Stress-Induced Responses in Dairy Cattle. *Animals*. 2023. Vol. 13(22). DOI: https://doi.org/10.3390/ani13223451

9. Hansen B., Li Y., Sun R., Schei I. Forecasting milk delivery to dairy–How modern statistical and machine learning methods can contribute. *Expert Systems with Applications*. 2024. Vol. 248. DOI: https://doi.org/10.1016/j.eswa.2024.123475

10. Hayes E., Wallace D., O'Donnell C., Greene D., Hennessy D., O'Shea N., Fenelon M. Trend analysis and prediction of seasonal changes in milk composition from a pasture-based dairy research herd. *Journal of Dairy Science*. 2023. Vol. 106(4). PP. 2326–2337. DOI: https://doi.org/10.3168/jds.2021-21483

11. Гладій М. Р., Просович О. П. Сучасний стан та перспективи розвитку молочної галузі України. *Вісник Національного університету «Львівська політехніка». Серія «Проблеми економіки та управління»*. 2022. № 2(6). С. 20–31. DOI: http://doi.org/10.23939/semi2022.02.020

12. Li M., Reed K., Cabrera V. A time series analysis of milk productivity in US dairy states. *Journal of Dairy Science*. 2023. Vol. 106(9). PP. 6232–6248. DOI: https://doi.org/10.3168/jds.2022-22751

13. Moore S., Costa A., Penasa M., Callegaro S., De Marchi M. How heat stress conditions affect milk yield, composition, and price in Italian Holstein herds. *Journal of Dairy Science*. 2023. Vol. 106(6). PP. 4042–4058. DOI: https://doi.org/10.3168/jds.2022-22640

14. Nosratabadi S., Ardabili S., Lakner Z., Mako C., Mosavi A. Prediction of food production using machine learning algorithms of multilayer perceptron and ANFIS. *Agriculture*. 2021. Vol. 11(5). DOI: https://doi.org/10.3390/agriculture11050408

15. O'Leary C., Lynch C. An evaluation of machine learning approaches for milk volume prediction in Ireland. *33rd Irish Signals and Systems Conferenc*e. 2022. PP. 1–8. DOI: https://doi.org/10.1109/ISSC55427.2022.9826160

16. Salamone M., Adriaens I., Vervaet A., Opsomer G., Atashi H., Fievez V., Hostens M. Prediction of first test day milk yield using historical records in dairy cows. *Animal*. 2022. Vol. 16(11). DOI: https://doi.org/10.1016/j.animal.2022.100658

17. Головне управління статистики в Хмельницькій області. URL: https://www.km.ukrstat.gov.ua/ukr/index.htm

18. Свиноус І., Ібатуллін М., Сало І., Радько В., Семсал А. Організаційно-економічні засади функціонування ринку молока. *Продовольчі ресурси*. 2022. Т. 10. №18. С. 276–286. DOI: https://doi.org/10.31073/foodresources2022-18-27

19. Ужва А. Аналітичний моніторинг стану виробництва молока в Україні. У*країнський журнал прикладної економіки та техніки*. 2024. Т. 9. № 2. С. 236–239. DOI: https://doi.org/10.36887/2415-8453-2024-2-40

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